Effects of winsorization: The cases of forecasting non-GAAP and GAAP earnings

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Abstract:

This study examines how the winsorization procedure affects the performance of regression-based earnings forecasting models. I find that the impact is multifaceted and depends principally on three factors: the level of data errors in the tails, the characteristics of firms affected by the process, and scaling. For a non-GAAP earnings yield specification, where data input errors exist, winsorization changes the information set in a non-systematic way and helps to improve the performance of regression-based forecasts, especially when the least squares estimator is employed. However, for a non-GAAP earnings per share specification, with fewer data input errors found in the tails of the distribution, winsorization has a particularly strong effect on very large companies, lowering the economic value of earnings predictions. I observe similar results for corresponding GAAP earnings specifications. Robust estimators, such as least absolute deviation, high breakdown-point and Theil-Sen, appear to be a more effective solution than winsorization. Their earnings forecasts consistently yield significant positive abnormal returns across non-GAAP and GAAP earnings specifications.

Keywords: Winsorization, earnings forecasts, scaling, robust regression, influential observations, stock returns.

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1. Introduction

"Sets of observations which have been de-tailed by over-vigorous use of a rule for rejecting outliers are inappropriate, since they are not samples."

Tukey (1960)

While econometric studies warn against the use of a winsorization process that replaces sample values above or below a given percentile of the sample distribution with the values at the respective percentiles, the majority of empirical accounting studies employ this process (Leone et al., 2017). Extreme observations/outliers in cross-sectional data used in these studies lead to biased coefficient estimates and heteroscedastic regression errors (Barth and Kallapur, 1996), and winsorization appears to be a simple and convenient solution. In cases where outliers occur due to shocks or data entry errors, winsorization helps to remove the effect of these observations (Leone et al., 2017). However, when extreme values are just reflections of the cross-sectional variation in firm characteristics such as firm size or profitability, this procedure risks systematically altering the data and any economic inferences for a subset of firms that may form important parts of investment strategies. Hence, it risks affecting the efficiency and usefulness of coefficient estimates.

This study seeks to shed light on these issues by addressing three questions. First, what is the extent and impact of data input errors in regression-based forecasts of earnings? Second, what is the impact of the winsorization process on the statistical performance of regression estimators? Third, how does winsorization affect the investment usefulness of earnings predictions?

I use the earnings forecast setting for several reasons. First, earnings forecasts are a key determinant of equity value (Ohlson, 1995; Ohlson and Juettner-Neuroth, 2005) and as such are important to investors in portfolio formation (Frankle and Lee, 1998; Hou et al., 2012). Although most investors rely on forecasts of financial analysts (Brown et al., 1987), many studies find that these are frequently biased (see e.g. Bradshaw et al., 2001; Dichev and

Tang, 2009; Frankel and Lee, 1998). Therefore, a great deal of research has been devoted to the development of bias free regression-based forecasts. These forecasting models frequently rely on winsorization to reduce the effect of observations with extreme values (e.g., Harris and Wang, 2013; Hou et al., 2012; So, 2013). Hence, while claiming to outperform the forecasts of financial analysts in terms of accuracy, their results may be limited to a specific sample and potential distortions by the winsorization process are largely ignored. Second, the use of earnings forecasts in the pricing of stocks and in portfolio formation (see e.g. Black et al., 2018; Bradshaw and Sloan, 2002; Bradshaw et al., 2018) allows us to look beyond conclusions offered by existing studies on winsorization, such as Leone et al. (2017), by also considering the impact of winsorization on economic values.

To begin, I examine the authenticity of archival GAAP and non-GAAP earnings data.[1] I manually check earnings figures in 10-K reports and find that the total GAAP earnings data downloaded from COMPUSTAT are highly reliable. Meanwhile, for non-GAAP earnings per share downloaded from the I/B/E/S database, the veracity of 49% of the data in the tails of the distribution is questionable, being more than double the corresponding GAAP earnings per share. Here, the role of winsorization might serve different purposes and it might have different effects. For the case of non-GAAP earnings that claim to consist of recurring items, winsorization might help remove data input errors, while for the case of GAAP earnings, it might help to remove non-recurring items.

To provide some insights into the nature of the data in the tails, I carry out a further investigation of the companies whose GAAP and non-GAAP earnings are likely to be replaced by winsorized values in a cross-sectional regression for both unscaled and scaled earnings (namely, total earnings, earnings per share and earnings yield). I find that, for the total earnings and for the earnings per share specifications, the upper tails of earnings

[1] Non-GAAP ("Street") earnings numbers are the figures announced by corporations in their press releases and tracked by analyst estimate clearinghouse services (Bradshaw and Sloan, 2002). They contain only the continuing component of GAAP earnings (Brown et al. 2015).

distributions consist of genuine earnings figures of many important corporations, such as General Motors, Berkshire Hathaway, General Electric, Exxon Mobil Corporation, and International Business Machines Corporation, all of which play a major role in capital market investment due to their prominence in typical portfolios. In these cases, replacing reported accounting figures with winsorized values that are more 'acceptable' introduces statistical bias and potentially misleading information about large and economically important companies. Earnings forecasts, therefore, may have less economic value even if they appear to have low forecast errors. However, scaling by market capitalization changes the distribution of earnings. Here, winsorization of companies in the tails appears to be non-systematic and the impact of winsorization on economic values is less likely to be serious.

I employ both GAAP and non-GAAP earnings forecasts to formally examine the effect of winsorization, with particular focus on the non-GAAP measure because of its availability, importance, and relevance to investors and other stakeholders (see e.g. Bentley et al., 2018; Black et al., 2018; Bradshaw and Sloan, 2002; Brown and Sivakumar, 2003; Hoogervorst, 2016; Wieland, Dawkins and Dugan, 2013). I use both unscaled and scaled earnings specifications including total earnings, earnings per share (EPS) and earnings yield (EY).[2] Along with the more common least square (LS) estimator, I employ two robust estimators, which are recommended in the econometric literature as methods for addressing outliers. These are the least absolute deviation (LAD) estimator by Edgeworth (1887) and the

[2] An investigation of prior earnings forecast, equity valuation and implied cost of capital studies reveals that the majority of these studies use earnings per share (e.g. Bradshaw et al., 2018; Gerakos and Gramacy, 2013, Haris and Wang, 2013; Li and Mohanram, 2014; So, 2013) due to its availability and direct use in equity valuation models. To my knowledge, while there are a few studies that look at total GAAP earnings (Gerakos and Gramacy, 2013; Hou et al., 2012; Li and Mohanram, 2014), there is no study that forecasts non-GAAP total earnings. Nevertheless, for completeness, I calculate non-GAAP total earnings by multiplying the non-GAAP earnings per share obtained from I/B/E/S database by the number of shares outstanding and replicate all empirical tests. I observe similar results to the case of non-GAAP earnings per share forecast. The results are available upon request.

high-breakdown point (MM) estimator by Yohai (1987).[3] Such estimators assign less weight to large residuals than the LS estimator and tend to reduce the impact of outliers (Verardi and Croux, 2009).[4] Here, there is a potential trade-off between reducing the effect of outliers and losing information. Leone et al. (2017) find that the MM estimator outperforms winsorization in providing efficient estimates of coefficients. In the context of forecasting earnings, efficient in-sample estimates might not always lead to outperformance in out-of-sample forecasts due to changes in the information set; as a result, the economic impact is unclear.

In order to assess the accuracy of forecasts, compared to Gerakos and Gramacy (2013), I employ several evaluation metrics, including forecast bias, absolute forecast error and root mean-squared error, recognizing that investors may have different loss functions.[5] Using the original sample, earnings forecasts based on the LS estimator are less accurate than those of the LAD and MM estimators. Winsorization appears to improve the forecast accuracy of the LS and LAD estimators, with little impact on the MM estimator. With winsorization, the LS estimator performs as well as the other estimators, and the estimation procedure choice is no longer as important, confirming the findings of Gerakos and Gramacy (2013). However, without more knowledge about the investors' loss function, the most appropriate minimization criterion is not obvious.[6]

I, therefore, explore another approach in order to provide a more meaningful comparison by looking at the economic consequences of using different estimation

[3] Some studies in the forecasting literature (Hughes et al., 2008; Boudt et al., 2014) have used the LAD estimator in predicting analysts' forecast errors, but they do not provide quantitative evidence of how this estimator improves forecasting performance.
[4] Details about the LS, LAD and MM estimators can be found in Appendix A.
[5] Gerakos and Gramacy (2013) use the root-mean-squared error, which is associated with a quadratic loss function. as the evaluation criterion. If investors have different loss functions, this evaluation criterion becomes irrelevant. Although classical models of portfolio choice assume a quadratic loss function for investors, this assumption is not supported by any economic or psychological models (Lambert, 2004). This places a limitation on the findings of Gerakos and Gramacy (2013).
[6] While studies report that financial analysts have linear (Basu and Markov, 2004) or asymmetric (Clatworthy et al., 2012) loss functions, there is little consensus in the literature about the loss-function of investors (Lambert, 2004).

procedures in making forecasts of earnings. Since earnings forecasts are primarily used in equity valuation models and portfolio decisions (Frankel and Lee, 1998), following the approach of Ball et al. (2015), I sort earnings forecasts into portfolios and assess their economic value through the performance of these portfolios. I find that the effects of winsorization vary according to the characteristics of firms in the regression, the presence of data errors, and the earnings specifications.

For the non-GAAP earnings per share specification, where the tail of the distribution consists of both authentic observations and data errors, winsorization systematically alters the information of large firms, lowering the economic value of earnings predictions. Here, using the original (unwinsorized) sample, the LAD and MM estimators provide more-accurate forecasts with a higher predictive power of future returns. A portfolio based on LAD forecasts has a monthly abnormal return of 110.6 basis points, which is significantly greater than those based on forecasts of analysts and other estimators. It is also significantly higher than those based on earnings forecasts using the winsorized sample.

For the non-GAAP earnings yield specification, where more data errors are observed in the tails, winsorization alters information in a less-systematic fashion and does not have a significant impact on the economic value of forecasts. Following winsorization, the LS estimator performs just as well as the LAD and MM estimators. Unlike the case of a non-GAAP earnings per share specification, here, forecasts of analysts and of all the regression-based models have similar economic value.

I observe similar results when I use alternative specifications of GAAP earnings, including total earnings, earnings per share, and earnings yield where the data are nearly free of entry errors. The effect of winsorization depends on which group of firms' earnings is altered, being more severe for the case of total earnings and earnings per share. Meanwhile, the MM estimator performs consistently well across all earnings specifications, regardless of the presence of extreme observations and data censoring choices. Again, I observe similar results when I use the non-parametric Theil-Sen estimator recommended by Ohlson and Kim (2015) and Kim and Ohlson (2018) as an additional test. Hence, these robust estimators appear to be a better remedy for cross-sectional regressions compared to winsorization.

This paper makes a threefold contribution to the literature. First, it provides novel evidence of the reliability of both GAAP and non-GAAP earnings archival data as well as the characteristics of firms in the tails of unscaled and scaled earnings distributions. Second, it is the first study to provide evidence of the impact of the winsorization process on economic values. Third, this study provides additional evidence on robust estimators that perform consistently well across earnings specifications and data treatments, complementing and extending the findings of Leone et al. (2017).

My findings have clear implications for future research regarding the need to examine the dataset before adjusting the data. Here, three factors need to be considered:

1) Data input errors: if the majority of the data in the tails are input errors, winsorization may be used without a significant impact.

2) Characteristics of the firms in the tails: Researchers should examine the importance of firms/observations in the tails before introducing artificial data.

3) Scaling: scaling helps in changing the distribution of earnings, but the impact of the winsorization process is still significant in the case of per-share earnings. It is insignificant in the case of earnings yield, i.e., here market capitalization seems to be a better deflator.

The remainder of this paper is organized as follows. Section 2 discusses the motivation and research design. Section 3 discusses data authenticity checks and presents preliminary tests. Section 4 shows the impact on forecast accuracy. Section 5 explores the impact on the economic value of earnings forecasts. Section 6 presents results related to the GAAP earnings. Section 7 discusses the performance of a non-parametric robust estimator, Theil-Sen. Section 8 provides summary conclusions.

2. Motivation and research design

2.1. Cross-sectional regression-based forecasting model

Non-GAAP earnings per share and analysts' earnings per share forecasts are widely used by both researchers and investors, since they are believed to contain only recurring items and, hence, to be more informative about firms' future performances (Black et al., 2018; Bradshaw et al., 2018; Bradshaw and Sloan, 2002; Hoogervorst, 2016). However, due to the well-documented bias and relatively low coverage of analysts' forecasts, researchers seek to either improve the forecasting performance and/or provide forecasts for young and small firms with few or no analysts following these firms.

At time t, in order to predict earnings at time $t+1$, researchers study the relationship between earnings and their determinants from a restricted information set ($\mathbf{IS}$) by performing cross-sectional regressions, as in equation (1) below:

$$e_{i,t}^{r} = \alpha + \boldsymbol{\beta} \times \mathbf{IS}_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where $e_{i,t}^{r}$ denotes reported earnings at time t of firm i, $\mathbf{IS}_{i,t-1}$ denotes the information vector at time $t-1$ of firm i, α is the intercept and $\varepsilon_{i,t}$ is the residual term. Here, earnings can be either un-scaled earnings (e.g. total earnings) or scaled earnings (e.g. earnings per share, forward earnings yield). Variables in the information vector are scaled accordingly.

Forecasts of earnings at time $t+1$ of firm i ($E_{i,t+1}^{f}$) are then estimated by using the estimated coefficients $\left\{\hat{\alpha}, \hat{\beta}\right\}$ and the information set $\mathbf{IS}_{i,t}$ at time t as in equation (2):

$$E^{f}_{i,t+1} = \hat{\alpha} + \hat{\boldsymbol{\beta}} \times \mathbf{IS}_{i,t} \tag{2}$$

Such forecasts ($E^{f}_{i,t+1}$) are widely used in equity valuation and asset valuation exercises. Their efficacy and economic value depend on the reliability of the estimated coefficients $\left\{\hat{\alpha}, \hat{\boldsymbol{\beta}}\right\}$. This, in turn, is determined by the distribution of earnings and the information set and the vulnerability of the estimators in the presence of outliers arising from the wide variation in firm size and characteristics. The use of robust estimators and scaling, however, could be a partial remedy to improve the efficiency and accuracy of coefficient estimates. An investigation of 20 studies on forecasting earnings and use of earnings forecasts (implied cost of capital, post earnings announcement drift) reveals that researchers mainly use the earnings per share specification and the LS estimator.[7]

The frequently used LS estimator, which minimizes the sum of squared residuals, gives a heavy weighting to extreme residuals. Hence, the presence of observations with extreme values leads to biased and inefficient LS estimates (Barth and Kullapur, 1996; Easton and Sommers, 2003; Rousseeuw and Leroy, 1987). This is most likely to occur in cross-sectional regressions in the absence of scaling due to data input errors and the business nature of large firms.[8] The winsorization process, which alters information in the tails and generates a better-behaved dataset, appears to be an easy solution. However, its impact is unpredictable. On the one hand, ruling out data input errors (in the case of non-GAAP earnings) might help to reduce the biases of LS estimates, improving the performance of this estimator. On the other hand, replacing authentic data observations by artificial ones (in the case of GAAP earnings), while appearing to reduce the biasness of the LS estimator and improve forecast accuracy, potentially reduces the economic performance of the predictions.

[7] For brevity, the survey results are not tabulated but are available upon request.
[8] On this topic, Abarbanell and Lehavy (2003) find that influential asymmetries in the tails can exaggerate or obscure the LS estimates, which can lead to different empirical findings and inferences.

Scaling, on the other hand, might change the distribution of earnings, improving the performance of the LS estimator and reducing the impact of winsorization. However, even scaling by market capitalization might not be sufficient to resolve the heteroscedasticity problem (Clatworthy et al., 2007). Therefore, robust estimators which are resilient to extreme observations might appear to be a better solution. This is discussed in detail in the next section.

2.2. Robust estimators and the effect of scaling

To address the non-normality of the distribution of cross-sectional data, econometricians have suggested robust estimators, such as the least absolute deviation (LAD) and the high breakdown-point (MM) estimators. These estimators, with symmetric and non-decreasing loss functions, give less weight to extreme residuals than LS. Hence, they reduce the impact of outliers and produce less biased, more consistent and more efficient estimates for $\left\{\hat{\alpha}, \hat{\boldsymbol{\beta}}\right\}$ (Leone et al., 2017; Verardi and Croux, 2009), potentially resulting in more accurate forecasts. More importantly, the coefficient estimates carry the information of the whole sample, including firms whose earnings are significantly higher/lower than the rest of the sample and which are potentially important in portfolio formation. Here, the winsorization, by introducing artificial data, might make the coefficient estimates of robust estimators less meaningful.

The distribution of the information set is affected by any scaling. For example, firms with the highest earnings figures tend to be large firms, whereas firms with the highest earnings yields tend to be firms with higher levels of risk or with depressed share prices. The economic impact of winsorization on earnings forecasts in the case of the earnings yield specification, therefore, may or may not be significant. While scaling, as a remedy to overcome the coefficient bias problem of cross-sectional regressions (Barth and Kallapur, 1996), might obviate the need for winsorization, the most appropriate scale factor is unknown.

Findings as to whether market capitalization is the best deflator are contradictory. Studies such as Lo and Lys (2000) and Easton and Sommers (2003) suggest that market capitalization is the best deflator. Earnings yield regressions, following this notion, should suffer less from variations in firm size. Hence, the LS estimator and other robust estimators might produce similar results in terms of both forecast accuracy and economic value, and the winsorization process is no longer needed. Barth and Clinch (2009), on the other hand, find that the market capitalization-deflated specification (e.g. earnings yield) does not perform as well as either the number of share-deflated (e.g. earnings per share) or un-deflated data (e.g. total earnings) in terms of the coefficient bias. Using UK data, Akbar and Stark (2003) confirm this finding. These results suggest that even for the earnings yield specification, the LS regression coefficient estimates might be inefficient and underperform those of the LAD and MM estimators.

In summary, the impact of the winsorization process appears to be complex, and it potentially depends on several factors, including the existence of data errors, the characteristics of firms in the tails of the distribution and the use of scaling. Whether robust estimators (LAD and MM) offer a better solution requires a careful and thorough examination.

2.3. Research design

The study employs the information set (i.e. independent variables) in Hou et al. (2012) to predict unscaled and scaled earnings. The earnings forecasts generated by this set are claimed to be more accurate and capture the market expectations better than those of analysts (Hou et al., 2012). This claim, however, ignores the non-comparability of earnings measures. Hou et al. (2012) predict GAAP earnings while analysts typically predict non-GAAP earnings. I, therefore, compare model-based forecasts with analysts' forecasts where they both predict non-GAAP earnings. I then compare these results with those of GAAP earnings forecasts.

I use three parametric estimators, LS, LAD and MM, in the earnings regression, as in equation (1) using both the original and the winsorized samples and for both the non-GAAP earnings per share and earnings yield specifications.[9] To facilitate direct comparison and portfolio formation, I adjust the earnings forecasts accordingly to produce the earnings yield, i.e., the earnings per share forecasts are eventually scaled by the share prices of the previous period.

The forecast error of firm i at time $t+1$ equals the actual reported earnings minus the forecasts of earnings, as in equation (3):

$$FE_{i,t+1} = e^{r}_{i,t+1} - E^{f}_{i,t+1} \tag{3}$$

where $e^{r}_{i,t+1}$ denotes the reported earnings of firm i at time $t+1$ and $E^{f}_{i,t+1}$ denotes the time $t+1$ earnings forecasts of firm i generated at time t.

I evaluate the accuracy of earnings forecast proxies based on a comparison of the means of forecast errors, absolute forecast errors and root-mean-squared errors.[10] Compared to the forecast error statistics, an absolute forecast error penalizes both positive and negative errors. Hence, it is considered by many to be a better evaluation measure of forecast accuracy. The regression-based model using the LS estimator, by design, aims to minimize the sum of squared errors. Hence, to provide a level playing field, I also use root-mean-squared errors (*RMSE*) as an evaluation criterion. However, these measures of accuracy are associated with different loss functions. Without more knowledge of investors' loss function, the economic interpretation of the results is limited.

[9] As discussed in footnote 4, for the case of the non-GAAP total earnings specification, results are similar to those of non-GAAP earnings per share and available upon request.
[10] For brevity, details of these measures are described in Appendix B.

Therefore, I focus on the investment usefulness of earnings forecasts to evaluate different estimators and the impact of the winsorization process. This approach is based on the theoretical pricing framework in Ohlson and Juettner-Nauroth (2005) in equation (4):

$$\frac{P_{i,t}}{EPS_{i,t+1}} = \frac{1}{r_i} \times \frac{g_i - (\gamma_i - 1)}{r_i - (\gamma_i - 1)} \tag{4}$$

where, for firm i, $P_{i,t}$ is the value of a stock at time t, $EPS_{i,t+1}$ is the expected earnings per share of that stock at time $t+1$, r_i is the cost of capital, g_i is the near-term growth rate of expected earnings per share, and $(\gamma_i - 1)$ is the long-run growth rate of abnormal earnings.

Transforming equation (4), the forward earnings yield ($\frac{EPS_{i,t+1}}{P_{i,t}}$) can be estimated as follows:

$$\frac{EPS_{i,t+1}}{P_{i,t}} = \frac{r_i \times [r_i - (\gamma_i - 1)]}{g_i - (\gamma_i - 1)} \tag{5}$$

In this form, the forward earnings yield is positively correlated with the cost of capital (r_i) which proxies for expected stock returns. Empirical evidence shows that the forward earnings yield performs as well as more-sophisticated proxies in capturing expected future stock returns (Easton and Monahan, 2005). Therefore, the more informative the earnings forecasts are about future stock returns, the higher the economic value they possess. I follow the approach in Novy-Marx (2013) and Ball et al. (2015) to sort earnings forecasts into quintile portfolios and assess the performance of these portfolios based on the monotonic trend of returns from the 1st to 5th quintile portfolios and on the performance of the high minus low portfolios.

3. Data authenticity check and preliminary tests

3.1. Data selection and summary statistics

The sample includes all firms traded on the NYSE, Amex and NASDAQ with December fiscal year ends and share-codes of 10 and 11 (excluding ADRs, closed-end funds and REITs). I obtain accounting information from COMPUSTAT, monthly stock returns and prices from CRSP, and analysts' forecasts and reported non-GAAP EPS from I/B/E/S. The study period is from 1983 to 2013 due to the low availability of analysts' forecasts prior to 1983. Details of the variables used in this study are presented in Appendix C.

I use only companies with December fiscal year ends in order to isolate the impact of seasonal effects on the market's reaction to earnings news and the different characteristics of firms with different fiscal year-ends (Smith Bamber et al., 2000). I collect analysts' April forecasts each year, allowing for a reporting lag of three months. This is to ensure the matching between the return window and the horizon of the expected earnings measure (approximately one year) as well as the aligning of analysts' forecast accuracy.[11] As a result, the sample accounts for approximately 55% of the whole population, limiting to some extent the generalizability of the findings.

I carry out empirical tests on both the original and winsorized samples. In the winsorized sample, all accounting information is winsorized with observations below the 1st percentile or above the 99th percentile being replaced by values at these percentiles. Analysts' forecasts are not winsorized.

Table 1 shows the time-series averages of variables on a per share basis. Panels A and B present statistics of the original and winsorized samples respectively. In panel A, the relatively higher numerical value of the means of the reported earnings compared with the median is driven by the extreme values (minimum and maximum) in the long-tailed distributions. The LS estimator is likely to generate biased estimates of the relationship between earnings and its determinants with such a distribution. Compared with Panel A,

[11] Since analysts' forecasts become more accurate towards the earnings announcement days (Ciciretti et al., 2009), selecting forecasts three months after the fiscal year end ensures alignment between forecasts.

Panel B shows that winsorization helps reduce the variability (standard deviation) and the skewness of the information set, potentially diminishing the biasness and inefficiency of the LS estimator.

<Insert Table 1 about here>

To examine the impact of influential observations of a single variable on the LS estimates, I first identify the residuals from a multivariate regression of earnings on independent variables, excluding the variable of interest. The residuals from the regression of the variable of interest on the same regressor set are also estimated. A plot of the first residuals on the second set of residuals shows the relationship between earnings and the variable of interest. Figure 1 plots residuals of non-GAAP earnings (ARE1) against residuals of lagged-one-year non-GAAP earnings (ARE) for just one randomly selected year (2005) using the original and winsorized samples.[12] In Figure 1.A, the observation in the bottom left corner is one of the influential/outliers. The coefficient of the lagged-one-year earnings variable is 8.00 in the presence of this extreme observation. As observed in Figure 1.B, replacing the value of this observation via winsorization significantly lowers the slope and reduces the reported coefficient. The new coefficient of lagged-one-year earnings is 0.74. This example illustrates the sensitivity of the LS estimates to the presence of extreme values. Although the winsorization process helps increase the accuracy of the LS estimates, it is still inefficient (Leone et al., 2017), and the economic impact of the LS estimates remains unexplored.

3.2. Data authenticity and characteristics of firms in the tails

While winsorization is helpful in ruling out the impact of data errors, there is limited evidence of their existence (Kraft et al., 2006). To address this, I randomly select 334 GAAP total earnings observations downloaded from the COMPUSTAT database which are in the

[12] Plots for other years are also available upon request.

tails of the earnings distribution (approximately 10% of the winsorized observations). I manually check them against the GAAP total earnings in the 10-K reports downloaded from SEC EDGAR. I find that GAAP earnings archival data are authentic, with 94.3% matching the reported figures (Table 2). Of the 334 observations checked, only two are data errors that are not aligned with the reported figures. I therefore use GAAP earnings as a benchmark for validating the non-GAAP ones.

An examination of 1076 observations at the tails of the non-GAAP EPS distribution shows a wide dispersion between them and GAAP EPS, supporting the finding of Bradshaw and Sloan (2002). In total, 49.3% of the non-GAAP figures are more than double the corresponding GAAP EPS figures, which could be a result of data input errors, supporting the findings of Ljungqvist et al. (2009) and Acker and Duck (2009). Of the remainder, 37% of the observations differ by less than 20% from the GAAP earnings. Clearly, the tails of the non-GAAP earnings distribution contain both authentic data and data errors. In this case, winsorization may be useful to rule out data input errors.

3.3. Characteristics of firms in the tails

Research in accounting and finance tends to apply the winsorization process without much knowledge of the nature of the observations in the tails of a distribution. Without such knowledge, the impact of the winsorization process is unpredictable. Hence, in order to provide insight into the characteristics of firms whose non-GAAP earnings are winsorized, I compare their average total assets and share price with those of the whole sample for each of the earnings per share and earnings yield specifications (see Panel A of Table 3). In Panel B of Table 3, I list the top ten most frequently appearing firms in the tail and their average total assets. The average differences (Diff) between their non-GAAP and GAAP earnings, scaled by GAAP earnings, serve as an indication of whether the corresponding observations are data input errors. Here, I assume that if Diff is greater than 1, it is a data input error.

For the non-GAAP earnings per share specification, winsorization alters the earnings figures of large firms with an average of total assets of $26,818 million, which is more than four times the sample average of $6,088 million. More than 10% of these firms have a share price of more than $266/share (see Table 3 Panel A), with potentially important implications for portfolio formation. The most frequently appearing firms in this tail include Berkshire Hathaway (25 out of 30 years of data: 25/30), General Motors (17/30), and Alleghany Corp (19/30) (see Table 3 Panel B). I also conclude that 5 out of the 10 firms appear in the list due to data input errors. This demonstrates that with the winsorization process, figures of large corporations are systematically replaced with what is effectively an arbitrary winsorized figure that contains limited information about the underlying company's performance. Hence, it potentially reduces the informativeness of the sample, ultimately affecting the information usefulness of the earnings predictions in the portfolio selection process.

In contrast, in the case of the non-GAAP earnings yield specification, winsorization alters figures of relatively smaller firms and penny stocks. The mean of the total assets of firms whose earnings yields are winsorized is just $1,796 million, which is significantly lower than that of the whole sample ($6,696 million). Approximately 50% of these firms are traded at a price of less than $6/share, and approximately 10% of the winsorized observations belong to penny stocks (P10=$1.1). Here, the median stock price of winsorized observations is just $5.8, compared with $14.66 in the case of the earnings per share specification (see Table 3 Panel A). Nine out of the 10 most frequently appearing firms encounter data input errors (see Table 3 Panel B). I surmise that the winsorization process is likely to have less of an impact on the economic value of earnings forecasts in the case of the earnings yield specification.

4. Impact on coefficient estimates and forecast accuracy

4.1. Earnings regression coefficients

Table 4 shows the coefficients obtained from regressing different measures of reported earnings on accounting variables, including the previous year's measure of earnings, total assets, dividends, a dividend paying indicator, a negative earnings indicator, and accruals, based on the original sample (under the column headed (1)) and on the winsorized sample (under the column headed (2)). Panels A and B show the results from the earnings per share and the earnings yield specifications, respectively. For both earnings specifications, winsorization changes the number of variables that make a statistically significant contribution to the regressions using the LS estimator. A comparison of the coefficients obtained from the original and winsorized samples (under the column headed (2)-(1)) illustrates the differences in the LS estimates. These differences in coefficients are mainly driven by the variability of LS coefficients associated with the original sample.[13] This remains the case even with the earnings yield specification. Hence, this latter method of scaling does not fully mitigate the coefficient bias problem caused by the size effects, supporting the findings of Barth and Clinch (2009).

<Insert Table 4 about here>

The values of the coefficients using the LAD estimator are more stable over the two earnings specifications in terms of both their magnitude and their statistical significance. However, several of the independent variables only become statistically significant after winsorization. Again, scaling does not always alleviate the size effect problem.

For the MM estimator, the magnitude, sign and statistical significance of the coefficients vary the least. With the earnings yield specification (Panel B), the coefficient estimates of the LS, LAD and MM estimators based on the winsorized sample seem similar to those of the MM estimator based on the original sample. The MM estimator's performance

[13] I do not focus on the significance of the coefficient differences, since the insignificance is driven by the variability of the coefficients, which itself illustrates the vulnerability of the estimator.

is consistent regardless of the sample specifications, and it potentially provides unbiased coefficient estimates, complementing findings of Leone et al. (2017). Meanwhile, winsorization appears to improve the efficiency of the LS and LAD estimated coefficients. I will examine how winsorization is translated into forecast accuracy and investment value of the earnings predictions in the next sections.

4.2. Forecast accuracy

I conduct a comparison of the forecast accuracy of analysts and regression-based models with the three different estimators (LS, LAD and MM) based on the common smaller sample of firm-year observations for which forecasts are available for both analysts and models.

Table 5 presents summary statistics of forecast errors, absolute forecast errors and root mean-squared errors associated with alternative forecasts using the original and the winsorized samples. Panels A and B show the results for the EPS specification while panels C and D present those of the EY specification. For comparison purposes, I scale EPS forecast errors by the share prices of the previous period to appear in the form of yields.

<Insert Table 5 about here>

In the original sample, the distributions of forecast errors are highly skewed, with long tails, inflating the mean forecast errors, absolute forecast errors and root-mean-squared errors, as shown in Panels A and C.[14] Not surprisingly, the LAD and MM estimators have the lowest mean absolute forecast error and the lowest root-mean-squared error. Thus, the LAD and MM estimators provide the more accurate forecasts. The LS estimator is inferior to the robust estimators even in terms of root-mean-squared errors for both the earnings per share and earnings yield specifications. By design, in the in-sample regressions, the LS estimator minimizes the sum of squared errors, the LAD estimator minimizes absolute forecast errors,

[14] The statistics associated with analysts' forecasts vary between the original and the winsorized samples because analysts' forecasts are assessed against the actual Wall Street earnings in the original sample, while the same forecasts are assessed against the winsorized value of Wall Street earnings in the winsorized sample.

and the MM estimator minimizes a more complex function of errors that gives residual weights that are in between the absolute and the square function, as specified in Appendix A. However, the distribution of the predictor set might be different in the out-of-sample period compared with the in-sample period. Hence, a model performing best in the in-sample period might not outperform others in the out-of-sample period. The poor performance of the LS estimator in terms of root mean-square error illustrates this, highlighting the importance of using the out-of-sample performance comparison in the earnings forecast context, an issue that is ignored by Leone et al. (2017). With the winsorized sample, the forecasts of the LAD and MM estimators are the most accurate, with the lowest absolute forecast errors, while LS becomes the most accurate model in terms of root mean-squared error.

There is a misalignment between the objectives of analysts and the evaluation method when using the winsorized sample where all figures are winsorized at the beginning (if one were to adopt the approach in Hou et al., 2012 and So, 2013). While analysts aim to forecast the actual non-GAAP earnings, the statistical comparison with regression-based models is based on winsorized values. This places an unfair disadvantage on analysts. Hence, for each earnings specification, I also show the results using a reduced sample in Panels B and D where errors associated with influential observations (which are winsorized in the winsorized sample) are removed to introduce a level playing field. Here, analysts' forecasts are as accurate as the best regression estimator. Winsorization improves the forecast accuracy for the LS and LAD estimators, while the impact on the MM estimator is insignificant.

The findings also demonstrate why different studies with different evaluation metrics and different censoring of the sample provide contradictory results. This emphasizes the need for an estimator that performs consistently well in the presence of anomalous observations. The LAD and MM estimators appear to be at least a partial answer to an improved statistical estimation of the parameters in the forecasting model. However, statistically superior performance does not necessarily imply superior economic performance. I explore this in the next section.

5. Impacts on the economic value of earnings forecasts

As outlined in Section 2, forward earnings yields are expected to be informative about, or a good proxy for, expected returns. The predictability of one-year-ahead stock returns, therefore, can be considered a measure of the economic value of earnings forecasts when evaluating the impact of winsorization. I first study the correlation between earnings forecasts and actual one-year-stock returns.[15] I then sort firms into portfolios based on the complete set of their earnings forecasts and analyse the performances of these portfolios.[16]

5.1. Relationship between earnings forecasts and one-year-ahead stock returns

Table 6 reports the relationship between one-year-ahead stock returns and the earnings forecasts of analysts (AF) and of the models (LS, LAD, MM).

<Insert Table 6 about here>

For the earnings per share specification (Panels A and B), the Pearson coefficients of the regression-based forecasts (LS, LAD, and MM) are positive but not statistically significant, while those of the analysts' forecasts have the wrong sign, although again not significant. On the other hand, using Spearman rank correlation coefficients, all earnings forecast proxies are significantly correlated with one-year stock returns. This suggests that based on the earnings forecasts of analysts and models, one can rank the relative future performance of stocks, but the actual noisy returns cannot be accurately predicted. I explore this issue more formally in the next section.

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[15] Again, I scale earnings forecasts to appear in the form of forward earnings yield.

[16] The results are similar when the portfolio selection and performance measurement are based on the winsorized sample, excluding winsorized observations. They are available upon request.

Based on the original sample, the Spearman rank correlation coefficients of the LAD and MM estimators are significantly higher than those of analysts and the LS estimator (Panel B). However, following winsorization, the LS estimator performs as well as the LAD estimator with a similar correlation coefficient with one-year ahead returns, and they are not significantly different from each other (Panel B). The winsorization process helps the LS estimator to produce less biased estimates, and it helps LS potentially improve the economic value of its forecasts. However, it has an insignificant effect on the performance of the LAD and MM estimators.

The results of the earnings yield specification (Panels C and D) are similar. Based on the original sample and Spearman ranks, analysts' forecasts are as informative as the LAD and MM estimators about one-year-ahead stock returns, and all are more informative than the LS estimator. Following winsorization, the LS estimator performs as well as the LAD and MM estimators and outperforms analysts in terms of the Spearman correlation coefficient with one-year-ahead stock returns.

5.2. Portfolio performance

To formally assess the economic value of forward earnings yield forecasts, I follow the approach in Novy-Marx (2013) and Ball et al. (2015) and sort earnings forecasts associated with analysts and regression-based models into five portfolios at the end of April each year after the analysts' forecasts and accounting information have been updated for December-fiscal-year-end firms and made publicly available. Higher forecasted forward earnings yields imply higher expected returns.[17] Hence, I expect to observe the monotonic increase in returns from the low to the high yield portfolios and that the high minus low portfolio will have

[17] For the earnings per share specification, earnings per share forecasts are scaled by share prices of the previous period.

positive returns.[18] A positive and significant abnormal return of the high minus low portfolio shows that earnings correlate with an underlying source of priced risk (Fama,1970) and are informative about future stock returns (Ball, 1978; Ball et al., 2009).[19]

Table 7 shows the value-weighted monthly returns of quintile portfolios and the abnormal returns after adjusting for systematic risk (the CAPM model) or for three Fama-French risk factors (Fama and French, 1993) for the earnings per share specification.[20] Panels A and B show the returns of portfolios based on the original sample and the winsorized sample, respectively. Note that the sample and the portfolios' returns are unchanged for analysts' forecasts.

<Insert Table 7 about here>

Here, the returns of portfolios associated with the LAD and MM estimators using the original sample increase monotonically. This implies that their earnings forecasts are informative about the future stock returns. The LAD high earnings forecast portfolio return is significantly higher than that of the low earnings forecast portfolio, even after adjusting for risk. The LAD high minus low portfolio has the highest monthly abnormal return of 110.6 basis points (108.1 basis points) based on the CAPM model (the Fama-French model) (Panel A Table 7). This is higher than those of the analysts (66.6 basis points - CAPM) and the other estimators (52.4 and 78.5 basis points for the LS and MM estimators, respectively). The differences between the LAD returns and those of the other estimators are statistically significant, as shown in Panel C of Table 7. After winsorization, the monotonically increasing trend of the LAD portfolios disappears, and the returns of the LAD high-minus-low portfolios here are lower than that of the LAD high-minus-low portfolio based on the original sample. This indicates that winsorization reduces the economic value of earnings per share

[18] The high portfolios consist of stocks in the highest quintile of forward earnings yield forecasts, while the low portfolios consist of stocks in the lowest quintile.
[19] Findings in Novy-Marx (2013) and Ball et al. (2015) suggest that firms' profitability is another risk factor, and this factor is included in the new Fama-French five-factor model (Fama and French, 2015).
[20] For brevity, only abnormal returns are presented. Beta coefficients are available upon request.

predictions, perhaps because it alters the information of several large firms that are important in portfolio formation.

The LS high-minus-low portfolio performs less well than the portfolio based on analysts prior to winsorization but is comparable to that of analysts and the other estimators following winsorization. Hence, if one uses the LS estimator, winsorization seems to be necessary to reduce the coefficient bias problem and to improve the economic value of its forecasts.

<Insert Table 8 about here>

Table 8 shows the value-weighted monthly returns of quintile portfolios and the abnormal returns after adjusting for systematic risk (the CAPM model) or for three Fama-French risk factors (Fama and French, 1993) based on the earnings yield specification.[21] There is no strictly monotonic increase in returns from portfolio 1 to portfolio 5 in any of the regression-based forecasts, as was observed in the case of the LAD and MM estimators with the earnings per share specification. The scaling by price process reduces the economic value of the earnings forecasts, possibly because scaling by price, which itself is a predictor of future earnings, to some extent neutralizes the information content of earnings predictions, complementing the findings of Clatworthy et al., (2007) that scaling might not be the best solution.

Based on the original sample (Panel A Table 8), the LAD and MM high minus low portfolios possess significant positive alphas that are higher than those of the LS estimator. However, following winsorization, the LS high-minus-low portfolio has higher alphas (Panel B Table 8), although the differences are statistically insignificant, as shown in Panel C of Table 8. Winsorization helps to improve the performance of the LS high-minus-low portfolio but has an insignificant impact on the performances of the LAD and MM estimators. This

[21] For brevity, only abnormal returns are presented. Beta coefficients are available upon request.

confirms the previous finding that if one uses the LS estimator, winsorization is essential to improve its performance.

I note that in Table 8, the alphas of the high minus low portfolios of all estimators are smaller than those of the analysts. However, the differences are not statistically significant, as shown in Panel D. The results hold for both the original and winsorized samples. This implies that although earnings yields based on analysts' forecasts may be inferior to those of some regression-based forecasts in terms of forecast error statistics, they appear to have similar economic value, questioning the usefulness of regression-based forecasting models. The LAD and MM estimators perform consistently well across earnings specifications, appearing to be a better solution than the winsorization process.

6. GAAP earnings: winsorization and forecasting

As discussed in section 3, there appears to be doubtful non-GAAP earnings figures in the I/B/E/S database, while the GAAP earnings from COMPUSTAT are nearly free from error. Hence, I replicate the empirical tests for three GAAP earnings specifications, namely, total earnings, EPS and EY. Here, winsorization replaces authentic data by artificial data that carry less economic information about the corresponding firms, potentially affecting the investment usefulness of the earnings forecasts.

6.1. Characteristics of firms in the tails

For the total earnings specification, winsorization alters the data of large firms, while it changes the data of smaller firms for the earnings yield specification (Table 9 Panel A).

<Insert Table 9 about here>

The top 5 most frequently appearing firms on the total earnings list are General Electric, Exxon Mobile, Intel Business Machines Corp, Coca-Cola and AT&T, which are not only large firms but are also among the most profitable (Table 9 Panel B). Being blue chip companies, they are valuable in investment strategies. Meanwhile, the most frequently appearing firms are a mixture of large and medium ones for the case of the earnings per share specification and a mixture of medium and small ones for the case of the earnings yield specification. Here, post-scaling by market capitalization, winsorization might not affect the portfolio performance in a systematic manner.

6.2. Forecast accuracy

As mentioned in section 2.3, to evaluate the accuracy of forecasts, I use three measures: mean forecast error (FE), mean absolute forecast error (AFE) and root mean squared error (RMSE). For comparison purposes, I subsequently deflate all unscaled and scaled earnings forecasts to be in the form of earnings yields. In terms of absolute forecast error, the LAD estimator, which minimizes the absolute error term, is the best performer except for the case of the earnings yield specification, where it underperforms the MM estimator (Table 10). Similar to the non-GAAP earnings results, the LS estimator, which minimizes the mean squared errors, underperforms other estimators even in terms of RMSE. This, again, illustrates that an estimator might perform well for the in-sample period but not necessarily for the out-of-sample period.

Note that for the earnings yield specification, the LAD and MM estimators are systematically upwardly biased with negative forecast errors, but they outperform the LS estimator in terms of absolute forecast errors. The systematic bias of the LAD and MM estimators potentially affects their performance.

<Insert Table 10 about here>

The winsorization process, in general, reduces the level of forecast errors, appearing to be a good choice to address the size effect in cross-sectional regressions. However, the economic impact of this process is less clear.

6.3. Portfolio performance

As outlined in Section 3, earnings forecasts are sorted into five portfolios. Table 11 reports the performance of the high-minus-low average monthly returns and abnormal returns (Fama French three-factor model). For the total earnings specification, as expected, winsorization, which alters information about large and important firms, reduces the economic value of the earnings forecasts, affecting portfolio performance (Table 11).

<Insert Table 11 about here>

For the earnings-per-share specification, the LS high-minus-low portfolio performs poorly in terms of economic value, with insignificant negative alphas, implying that scaling by the number of shares does not eliminate the size effects. While winsorization does not improve the economic value of the LS earnings forecasts, it enhances the economic performance of the LAD estimator. The MM estimator performs consistently well in both the original and the winsorized samples in terms of economic value although winsorzation marginally reduces the high-minus-low portfolio's abnormal return.

For the earnings yield specification, using the original sample, the LAD and MM estimators outperform the LS estimator in terms of economic value. However, winsorization enhances the economic value of LS earnings forecasts yet marginally reduces those of the LAD and MM's forecasts. The LS high minus low portfolio yields the highest alpha, although it is not significantly higher than the returns of the LAD and MM high minus low portfolios.

In short, the results based on GAAP earnings are similar to those based on non-GAAP earnings. For the total GAAP earnings specification, winsorization alters the information of large firms and reduces the investment usefulness of earnings forecasts. Meanwhile, for the earnings yield specification, with winsorization altering the data in a non-systematic fashion, winsorization does not have a significant impact on the economic performance of earnings forecasts. The MM estimator performs consistently well across all earnings specifications and when using either the original or winsorized samples. The performance of the LAD estimator, although better than the LS estimator, is not as consistent as that of the MM estimator. Here, the MM estimator appears to be a better solution than winsorization in addressing extreme observations in cross-sectional regressions.

7. Alternative non-parametric robust estimator

Ohlson and Kim (2015) and Kim and Ohlson (2018) apply a non-parametric robust estimation approach developed by Theil (1950) and Sen (1968) (hereafter, TS estimator) to estimate linear models in archival accounting research. In contrast to the parametric estimators where the lost functions are specified, this non-parametric estimator does not fixate on any specific function but fits a line to sample points by choosing the median of the slopes of all lines through pairs of points.[22] Ohlson and Kim (2015) and Kim and Ohlson (2018) compare the relative efficiency of the LS and TS estimator in cross-sectional valuation settings. They find that the TS estimator outperforms the LS one in terms of both the inter-temporal stability of estimated coefficients and the goodness-of-fit. I, therefore, carry out additional empirical investigations using the TS estimator and compare it with the LS, LAD and MM estimators.[23] Complementing the findings of Ohlson and Kim (2015) and Kim and Ohlson (2018), I find that the TS estimator performs consistently well in cross-sectional regressions even when extreme values are present. In general, its performance is similar to that of the MM estimator. The estimated coefficients associated with the TS estimator are similar for both original and winsorized samples, outperforming the LS and LAD estimators in terms of stability of estimated coefficients across different earnings specifications and measures. Earnings forecasts associated with the TS estimator are more accurate with higher economic value than those associated with the LS estimator. Furthermore, the winsorization

[22] See Ohlson and Kim (2015) for more detail about this model.

[23] I am grateful to Seil Kim for kindly providing me with access to his SAS code for the TS estimator.

process has minimal impact on the performance of earnings forecasts associated with the TS estimator in terms of accuracy and economic value.[24] Therefore, the TS estimator also appears to be a more effective solution than winsorization, though not significantly better than the easy to apply MM estimator.

8. Conclusion

This paper examines the usefulness, problems and pitfalls of winsorization regarding the performance of regression-based earnings forecasting models, especially the impact on the economic value of earnings predictions, using alternative regression criteria and different measures of earnings.

I find that the effect of the winsorization process depends on the extent to which data errors exist, the characteristics of firms in the tails and the regression estimator used. An investigation of the authenticity of archival data show that GAAP earnings data are highly reliable, while approximately 49 % of the data in the tails of the non-GAAP EPS distribution seem suspect.

When winsorization distorts the sample by systematically omitting authentic accounting data of major corporations, as in the cases of the total GAAP earnings and the non-GAAP earnings per share, winsorization appears to improve the forecast accuracy but lowers the economic value of any earnings predictions.

However, when winsorization alters data in a less-systematic fashion and helps to remove data errors, as in the case of the non-GAAP earnings yield specification, it does not have any significant impact on the economic value of earnings forecasts. Here, it enhances the performance of the LS estimator. For the case of the non-GAAP earnings yield specification, analysts' forecasts have higher economic value than the earnings forecasts of

[24] For brevity, I do not include the results in the paper. However, they are available upon request.

regression-based models, although the differences are statistically insignificant. Any attempts by modelers to forecast non-GAAP earnings yields appear to be of doubtful economic value.

I find that robust estimators such as least absolute deviation (LAD), high breakdown point (MM) and Theil-Sen (TS) perform consistently well, even in the presence of outliers and the use of different data treatments. Portfolios based on these three models can generate significant positive abnormal returns. These findings hold in the case of both non-GAAP and GAAP earnings measures.

In summary, studies on earnings forecasts need to carefully consider the effect of the winsorization process used to ensure the validity of their findings, with more attention devoted to understanding the characteristics of firms in the tails before making data adjustments. An investigation limited to the forecast accuracy or the efficiency of the coefficient estimate may not paint the whole picture. Without knowledge about the investors' loss function, evaluation of the statistics of the forecasting errors' properties remains subjective; interpretation based on economic criteria is potentially more valid. This is particularly relevant when a comparison with the forecast performance of analysts is being made. Robust estimators such as LAD, MM and TS perform consistently well even in the presence of extreme observations and across all earnings specifications. They offer a better solution than the winsorization process in dealing with outliers, and they are strongly recommended to be employed in studies using cross-sectional regressions.

Appendix A: Regression estimators

To estimate the parameters $(\alpha, \boldsymbol{\beta})$ in equation (1), the ordinary least squares estimator (LS) minimizes the sum of the squared residuals:

$$(\hat{\alpha}, \hat{\boldsymbol{\beta}})_{LS} = \arg \min_{\alpha, \boldsymbol{\beta}} \sum_{i=1}^{n} \varepsilon_i^2(\alpha, \boldsymbol{\beta}) \tag{A.1}$$

The LAD estimator proposed by Edgeworth (1887) minimizes the sum of the absolute values of the residuals rather than the sum of their squares:

$$(\hat{\alpha},\hat{\boldsymbol{\beta}})_{LAD} = \arg\ \min_{\alpha,\boldsymbol{\beta}} \sum_{i=1}^{n} \left| \varepsilon_i \left(\alpha,\boldsymbol{\beta}\right) \right| \tag{A.2}$$

The MM estimator developed by Yohai (1987) has a Tukey-Biweight loss-function that is even, non-decreasing for positive values and less increasing than the square function, and residuals are scaled by a fixed measure of dispersion:

$$(\hat{\alpha},\hat{\boldsymbol{\beta}})_{MM} = \arg\ \min_{\alpha,\boldsymbol{\beta}} \sum_{i=1}^{n} \rho\left(\frac{\varepsilon_i(\alpha,\boldsymbol{\beta})}{\hat{\sigma}^S} \right) \tag{A.3}$$

where $\hat{\sigma}^S$ is the fixed measure of dispersion and satisfies:

$$\frac{1}{n}\sum_{i=1}^{n} \rho\left(\frac{\varepsilon_i\left(\alpha,\boldsymbol{\beta}\right)}{\hat{\sigma}^S} \right) = b \tag{A.4}$$

where $b = E\left[\rho\left(Z\right)\right]$ with Z being normally distributed with mean 0 and variance of 1 and the loss function ρ is a Tukey-Biweight function as follows:

$$\rho\left(u\right) = \begin{cases} 1-\left[1-\left(\dfrac{u}{k}\right)^2\right]^3 & \text{if } \left|u\right| \le k \\ 1 & \text{if } \left|u\right| > k \end{cases} \tag{A.5}$$

where k=1.547 in the first step (equation (A.4)) and k=2.697 in the second step (equation (A.5)) for the efficiency of the MM-estimator of 70%.

Appendix B: Forecast accuracy valuation metrics

Forecast error: The forecast error at time $t+1$ of each model is measured as the mean forecast error:

$$FE_{t+1} = \frac{1}{n}\sum_{i=1,n} FE_{i,t+1} \tag{B.1}$$

where i denotes firm and n is the number of firms at time $t+1$ and $FE_{i,t+1}$ equals actual earnings minus earnings forecasts as in equation (3).

The time series-average forecast error of each model for a T-year out-of-sample period is then estimated as follows:

$$FE = \frac{1}{T} \sum_{t=0,T-1} FE_{t+1} \tag{B.2}$$

A positive forecast error implies a downward (pessimistic) bias in the forecast, while a negative forecast error demonstrates an upward (optimistic) bias.

Absolute forecast error: The absolute forecast error of firm i at time $t+1$ equals the absolute (modulus) of the corresponding forecast errors:

$$AFE_{i,t+1} = \left| FE_{i,t+1} \right| \tag{B.3}$$

The time series average absolute forecast error is then estimated in the same way as the forecast bias.

Root-mean-squared error: The annual *RMSE* is estimated as follows:

$$RMSE_{t+1} = \sqrt{\frac{1}{n} \sum_{i=1,n} FE^2_{i,t+1}} \tag{B.4}$$

where n is the number of firms at time $t+1$.

The time-series average of root-mean-squared errors is as follows:

$$RMSE = \frac{1}{T} \sum_{t=0,T-1} RMSE_{t+1} \tag{B.5}$$

where T is the number of years of the out-of-sample period and $RMSE_{t+1}$ is the annual root mean-squared error at time $t+1$.

Appendix C: Variable descriptions

This table shows the variables used in this study. Panel A presents items downloaded from CRSP/COMPUSTAT and I/B/E/S. Panel B describes the derived variables.

Panel A: Variables from databases

Variables	**Descriptions**	**COMPUSTAT/ CRSP Items**	**I/B/E/S Items**
AST	Assets-Total	AT	
DVC	Dividends for common equity-Total	DVC	
CSHO	Common shares outstanding	CSHO	
DP	Depreciation and amortization	DP	
ACT	Current assets-Total	ACT	
LCT	Current liabilities-Total	LCT	
DLC	Debt in current liabilities - Total	DLC	
TXP	Income taxes payable	TXP	
CEQ	Common /ordinary equity –Total	CEQ	
CHE	Cash and short-term investments	CHE	
IB	Income before extraordinary items	IB	
OANCF	Operating activities net cash flow	OANCF	
TCAP	Market capitalization	TCAP	
APRC	Adjusted stock price (end of March)	ADJPRC	
ASHO	Adjusted number of outstanding shares (end of March)	ADJSHR	
RET	Monthly returns	RET	
ARE	Actual reported earnings per share		EPS
EAF	Analysts' forecast (in April)		IBH.EPS

Panel B: Derived variables

	Descriptions
AT	Total assets deflated by the adjusted number of shares outstanding
DVD	Total dividends deflated by the adjusted number of shares outstanding
DD	Indicator for dividend payer, which is one if the dividend is positive and zero otherwise
NEG	Negative earnings indicator, which is one if earnings is negative and zero otherwise
ACR	Accruals: Prior to 1988, operating accruals per share are the changes in non-cash current assets less the changes in current liabilities excluding the changes in short-term debt and the changes in taxes payable minus depreciation and amortization expense deflated by the adjusted number of shares outstanding. For 1988 and after, accruals are estimated using the cash flow statement method as the difference between earnings and cash flows from operations deflated by the adjusted number of shares outstanding.

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Table 1: Descriptive statistics

This table shows the time series average statistics of variables on a per share basis that are used in the regression-based earnings forecast model. Panel A shows the statistics of the original sample (no winsorization) while Panel B presents those of the winsorized sample where accounting information is winsorized at the 1st and 99th percentiles.

Panel A: Original sample						
	Mean	Median	Min	Max	SD	Skewness
ARE – Non-GAAP EPS ($)	-755	0.6	-1666374	62756.59	36221.67	-7.32
AT – Assets per share ($)	86.93	15.17	0.09	103733.2	2303.96	35.07
DVD – Dividends per share ($)	0.29	0.04	0	22.21	0.86	12.8
DD – Dividend paying indicator	0.47	0.31	0	1	0.48	0.09
NEG - Negative earnings indicator	0.2	0	0	1	0.39	1.58
ACR – Accruals per share ($)	-1.82	-0.54	-1478.75	197.11	38.1	-10.9
N – Number of observations	46682					
Panel B: Winsorized sample						
	Mean	Median	Min	Max	SD	Skewness
ARE – Non-GAAP EPS ($)	0.67	0.6	-8.91	5.9	1.69	-1.31
AT - Assets per share ($)	32.83	15.17	0.42	319.29	50.03	3.4
DVD – Dividends per share ($)	0.27	0.04	0	2.46	0.47	2.54
DD – Dividend paying indicator	0.47	0.31	0	1	0.48	0.09
NEG - Negative earnings indicator	0.2	0	0	1	0.39	1.58
ACR – Accruals per share ($)	-1.13	-0.54	-13.19	4.93	2.37	-2.12
N – Number of observations	46682					

Table 2: Data authenticity

This table presents the matching level between the earnings figures in 10-K reports and those provided by data providers. Panel A shows the statistics of 334 randomly selected GAAP earnings figures that are in the bottom and top one percentile of the total GAAP earnings distribution. Panel B shows the level of earnings differences (%) of observations in the top and bottom one percentile of the non-GAAP EPS distribution that are equal to non-GAAP EPS minus GAAP EPS divided by the absolute of GAAP EPS.

Panel A: Extreme total GAAP earnings from COMPUSTAT (N=334)		
	N	%
Matched 10-K report	315	94.3%
Minor difference due to unclear adjustment	20	6.0%
Data error	2	0.6%
Panel B: Extreme Non-GAAP EPS observations from I/B/E/S (N=1076)		
	N	%
Difference between Non-GAAP and GAAP EPS		
Less than or equal 20%	398	37.0%
Between 20% and 50%	103	9.6%
Between 50% and 100%	44	4.1%
Greater than 100%	531	49.3%

Table 3: Statistics of extreme observations: Non-GAAP earnings

Panel A of this table presents the summary statistics of the total assets (AST) of the whole sample and of the total assets (AST) and share price (APRC) of observations whose non-GAAP earnings per share and earnings yield are winsorized. Panel B shows the top ten companies appearing in the tails most frequently. Freq denotes the number of years (out of 30) that the earnings of corresponding companies are winsorized. Diff denotes the average difference where difference equals non-GAAP earnings minus GAAP earnings divided by GAAP earnings. Error equals "Yes" if Diff is greater than one and "No" otherwise.

Panel A: Total assets (AST in $mil) and Share price (APRC in $)

	Mean	Median	Min	P10	P90	Max	N
Earnings per share							
AST (Whole sample)	6088	425.5	0.4	38.1	7577.0	2265792	46682
AST (Winsorized observations)	26818	839.7	1.9	9.8	26487.0	1009569	805
APRC (Winsorized observations)	1905	14.7	0.2	2.1	266.0	141600	805
Earnings yield							
AST (Whole sample)	6696	500.2	0.4	41.6	8618.3	2265792	41388
AST (Winsorized observations)	1796	114.0	0.4	12.4	3478.9	104270	657
APRC (Winsorized observations)	13	5.8	0.1	1.1	25.0	1511	657

Panel B: Companies whose non-GAAP earnings are winsorized

	Freq	AST ($Mil)	Diff	Error
Earnings per share				
Berkshire Hathaway	25	427452	-0.3	No
Trans-lux Corp	21	51	15.4	Yes
Alleghany Corp	19	22808	0.1	No
Fansteel Inc/de	17	112	6530.2	Yes
General Motors Co	17	91047	-0.1	No
Marlton Technologies	16	26	1617.5	Yes
National Western Life	16	6786	0.0	No
Signature Group holdings Inc	16	12891	8.4	Yes
Bell Industries Inc	14	62	19248.7	Yes
NVR Inc	14	2605	-0.1	No
Earnings yield				
	Freq	AST ($m)	Diff	Error
Trans-lux Corp	20	51	13.6	Yes
Fansteel Inc/de	16	112	5729.9	Yes
Marlton Technologies	16	26	1693.4	Yes
Signature Group holdings Inc	15	12891	11.2	Yes
Bell Industries Inc	13	62	19828.3	Yes
Carver Corp/wa	11	8	483075.6	Yes
Raytech Corp	10	189	-0.3	No
Essex Corp	9	5	133.3	Yes
American Biltrite Inc	8	295	88.6	Yes
MRV Communications Inc	8	261	2.6	Yes

Table 4: Earnings regression coefficients: Non-GAAP earnings

This table presents the time-series averages of the coefficients obtained from the Fama-Macbeth cross-sectional regressions of reported earnings ($e^r_{i,t}$) on the information set ($\mathbf{IS}_{i,t-1}$) with three different estimators: ordinary least squares (LS), least absolute deviation (LAD) and high breakdown-point (MM):

$$e^r_{i,t} = \alpha + \boldsymbol{\beta} \times \mathbf{IS}_{i,t-1} + \varepsilon_t$$

The information set includes lagged-one-year earnings per share (ARE), total assets per share (AT), total dividends per share (DVD), dividend paying indicator (DD), negative earnings indicator (NEG) and total accruals per share (ACR). For the earnings yield specification (EY), accounting information is scaled by firms' market capitalization of the previous period (i.e. AREY, ATY, DVDY and ACRY). Panels A and B show the results based on the earnings per share and earnings yield specifications, respectively. Column (1) presents results for the original sample while column (2) presents results for the winsorized sample.

Panel A: Regression coefficient- Earnings per share

	LS			LAD			MM		
	(1)	(2)	(2)-(1)	(1)	(2)	(2)-(1)	(1)	(2)	(2)-(1)
ARE	1.20***	0.695***	-0.509	0.777***	0.888***	0.111	1.026***	1.018***	-0.008
t-stat	*(3.28)*	*(19.64)*	*(-1.28)*	*(3.91)*	*(30.35)*	*(0.47)*	*(104.34)*	*(77.74)*	*(-1.16)*
AT	-0.93	0.000	0.929	0.005	0.001	-0.004	0.000	0.000	0.000
t-stat	*(-1.12)*	*(-0.46)*	*(1.07)*	*(1.43)*	*(1.58)*	*(-0.90)*	*(0.72)*	*(0.38)*	*(-0.60)*
DVD	26.3	0.227***	-26.0	0.022	0.067**	0.045	-0.040***	-0.035**	0.005
t-stat	*(0.96)*	*(4.65)*	*(-0.91)*	*(0.19)*	*(2.61)*	*(0.37)*	*(-3.05)*	*(-2.76)*	*(0.52)*
DD	-113.8	0.138***	113.9	0.080*	0.045***	-0.035	0.017**	0.018*	0.001
t-stat	*(-0.54)*	*(3.39)*	*(0.54)*	*(1.95)*	*(4.09)*	*(-0.97)*	*(2.60)*	*(1.92)*	*(0.37)*
NEG	-276	-0.12**	275.8	-0.013	0.056	0.069	0.147***	0.134***	-0.013**
t-stat	*(-1.19)*	*(-2.39)*	*(1.20)*	*(-0.06)*	*(1.56)*	*(0.28)*	*(3.34)*	*(3.20)*	*(-2.32)*
ACR	64.215	-0.043***	-64.26	-0.02	-0.03***	-0.010	-0.02***	-0.02***	-0.003
t-stat	*(0.92)*	*(-6.24)*	*(-0.89)*	*(-0.76)*	*(-10.21)*	*(-0.53)*	*(-4.19)*	*(-4.70)*	*(-1.51)*
Intercept	113.10	0.08**	-113.03	0.01	0.06***	0.05	0.038***	0.041***	0.003
t-stat	*(0.53)*	*(2.00)*	*(-0.53)*	*(0.17)*	*(6.41)*	*(0.76)*	*(4.97)*	*(4.68)*	*(0.74)*
$AdjR^2$	0.813	0.548							
N	46682	46682		46682	46682		46682	46682	

Panel b: Regression coefficient – Earnings yield

	LS			LAD			MM		
	(1)	(2)	(2)-(1)	(1)	(2)	(2)-(1)	(1)	(2)	(2)-(1)
AREY	1.852**	0.608***	-1.244	1.768**	0.598***	-1.171	0.576***	0.584***	0.008
t-stat	*(2.15)*	*(10.79)*	*(-1.36)*	*(2.03)*	*(22.77)*	*(-1.26)*	*(25.44)*	*(23.00)*	*(0.60)*
ATY	1.682	-0.001	-1.683*	-0.003	0.001	0.004	0.001***	0.001***	0.000
t-stat	*(1.33)*	*(-1.37)*	*(-1.75)*	*(-0.81)*	*(0.99)*	*(0.94)*	*(3.31)*	*(3.96)*	*(0.85)*
DVDY	25.13	0.070	-25.06	-0.291	0.054	0.344	0.055**	0.047	-0.008
t-stat	*(0.53)*	*(1.01)*	*(-0.52)*	*(-1.07)*	*(1.38)*	*(1.21)*	*(2.03)*	*(1.31)*	*(-0.66)*
DD	-37.13	0.018***	37.15	0.009**	0.007**	-0.002	0.005***	0.005***	0.000
t-stat	*(-0.83)*	*(4.42)*	*(0.82)*	*(2.15)*	*(5.72)*	*(-0.42)*	*(4.85)*	*(3.81)*	*(-0.58)*
NEG	-144.90*	-0.037***	144.87*	0.087	-0.022**	-0.108	-0.016***	-0.016***	0.000
t-stat	*(-1.70)*	*(-4.56)*	*(1.91)*	*(0.98)*	*(-4.65)*	*(-1.13)*	*(-3.93)*	*(-4.09)*	*(0.23)*
ACRY	13.539	-0.055***	-13.594	-0.032*	-0.033**	-0.001	-0.020***	-0.026***	-0.006***
t-stat	*(0.20)*	*(-3.96)*	*(-0.21)*	*(-1.90)*	*(-7.79)*	*(-0.05)*	*(-4.84)*	*(-5.98)*	*(-2.57)*
Intercept	22.98	0.004	-22.97	-0.041	0.016***	0.057	0.019***	0.018***	-0.001
t-stat	*(0.69)*	*(0.65)*	*(-0.69)*	*(-0.96)*	*(8.30)*	*(1.23)*	*(15.18)*	*(13.93)*	*(-1.14)*
$AdjR^2$	0.819	0.393							
N	41388	41388		41388	41388		41388	41388	

Table 5: Forecast errors: Non-GAAP earnings

This table presents the time-series averages of forecast errors (FE), absolute forecast errors (AFE) and root mean squared errors (RMSE), where the errors equal firms' reported earnings minus earnings forecasts (Panels A and C). They are scaled by the firm's share price for the case of earnings per share specification, and there is no scaling for the case of the earnings yield specification. Panels B and D present the statistics where errors associated with influential observations (which are winsorized in the winsorized sample) are removed from both the original and winsorized samples for comparison purposes (the reduced sample).

Panel A: Earnings per share specification - Forecast errors

	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
FE	28.15	43.32	21.51	20.71	96.4	-0.006	-0.011	-0.008
t-stat	*(0.43)*	*(1.33)*	*(0.52)*	*(1.10)*	*(0.99)*	*(-1.10)*	*(-2.49)*	*(-1.57)*
AFE	134.27	162.59***	106.82**	59.33**	171.9	0.073***	0.067***	0.068***
t-stat	*(1.46)*	*(3.39)*	*(2.42)*	*(1.99)*	*(1.41)*	*(8.07)*	*(7.51)*	*(7.46)*
RMSE	5200	3800***	3700***	2100**	6602.9***	0.254***	0.263***	0.280***
t-stat	*(1.59)*	*(3.05)*	*(2.75)*	*(2.41)*	*(1.56)*	*(6.25)*	*(5.65)*	*(5.65)*
N	39503	39503	39503	39503	39503	39503	39503	39503

Panel B: Earnings per share specification - Forecast errors (Reduced sample)

	Reduced original sample				Reduced winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
FE	-0.026***	9.32	0.00	0.00	-0.026	-0.002	-0.008**	-0.006
t-stat	*(-5.65)*	*(0.65)*	*(0.23)*	*(-0.12)*	*(-5.65)*	*(-0.44)*	*(-2.44)*	*(-1.51)*
AFE	0.048***	58.23*	0.12***	0.07***	0.048***	0.065***	0.059***	0.061***
t-stat	*(11.80)*	*(1.95)*	*(5.57)*	*(7.80)*	*(11.80)*	*(8.22)*	*(7.74)*	*(7.68)*
RMSE	0.243***	188.44	0.54***	0.38***	0.243***	0.199***	0.206***	0.228***
t-stat	*(4.70)*	*(1.62)*	*(3.60)*	*(3.21)*	*(4.70)*	*(5.99)*	*(5.63)*	*(5.68)*
N	38945	38945	38945	38945	38945	38945	38945	38945

Panel C: Earnings yield specification - Forecast errors

	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
FE	91.41	94.26**	65.04	-10.68	105.28	0.002	-0.010***	-0.012***
t-stat	*(0.87)*	*(2.52)*	*(1.63)*	*(-2.39)*	*(0.96)*	*(0.51)*	*(-3.41)*	*(-4.44)*
AFE	180.41	155.63***	104.91***	20.89***	183.84***	0.069***	0.061***	0.060***
t-stat	*(1.31)*	*(3.12)*	*(2.83)*	*(2.67)*	*(1.29)*	*(9.03)*	*(10.83)*	*(11.03)*
RMSE	6575.59	3584.10**	3579.63**	601.44***	6662.64***	0.146***	0.131***	0.129***
t-stat	*(1.45)*	*(2.29)*	*(2.26)*	*(3.11)*	*(1.45)*	*(8.32)*	*(11.76)*	*(11.69)*
N	34703	34703	34703	34703	34703	34703	34703	34703

Panel D: Earnings yield specification - Forecast errors (Reduced sample)

	Reduced original sample				Reduced winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
FE	-0.048***	27.94*	0.00	-0.01***	-0.048***	0.003	-0.008***	-0.010***
t-stat	*(-7.43)*	*(1.69)*	*(-0.66)*	*(-3.94)*	*(-7.43)*	*(0.65)*	*(-3.00)*	*(-4.10)*
AFE	0.080***	51.47*	0.15***	0.06***	0.080***	0.062***	0.056***	0.055***
t-stat	*(22.58)*	*(1.74)*	*(3.68)*	*(10.54)*	*(22.58)*	*(8.99)*	*(10.54)*	*(10.85)*
RMSE	0.253***	88.59	0.40***	0.12***	0.253***	0.116***	0.106***	0.104***
t-stat	*(3.33)*	*(1.81)*	*(2.86)*	*(10.27)*	*(3.33)*	*(9.89)*	*(12.82)*	*(13.02)*
N	34316	34316	34316	34316	34316	34316	34316	34316

Table 6: Correlation between earnings forecasts and one-year-ahead stock returns: Non-GAAP earnings

This table shows the relationship between one-year-ahead stock returns and earnings forecasts associated with analysts (AF) and regression estimators (LS, LAD and MM). Earnings per share forecasts are scaled by share prices of the previous period to appear in the form of earnings yield. Panel A shows the time-series averages of the correlations, while Panel B presents the significance of the differences between the correlation coefficient of the row earnings proxies and those of the column earnings proxies. For the earnings yield specification, Panel C shows the time-series averages of the correlations, while Panel D presents the significance of the differences between the correlation coefficients of the row earnings proxies and those of the column earnings proxies.

Panel A: Earnings per share specification - Pearson (CO1) and Spearman (CO2) Correlations								
	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
CO1	-0.006	0.018	0.010	0.008	-0.006	0.013	0.013	0.010
t-stat	*(-0.86)*	*(0.87)*	*(1.52)*	*(1.18)*	*(-0.86)*	*(0.72)*	*(0.84)*	*(0.73)*
CO2	0.068***	0.049**	0.105***	0.101***	0.068***	0.118***	0.111***	0.104***
t-stat	*(2.93)*	*(2.08)*	*(4.95)*	*(5.31)*	*(2.93)*	*(5.16)*	*(5.50)*	*(5.58)*
N	39503	39503	39503	39503	39503	39503	39503	39503
Panel B: Earnings per share specification- Test significance of the Spearman correlation differences								
	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
LS	0.019				-0.049***			
	(0.73)				*(-4.05)*			
LAD	-0.037**	-0.056**			-0.043***	0.006		
	(-2.34)	*(-2.47)*			*(-4.01)*	*(1.21)*		
MM	-0.032***	-0.051**	0.004		-0.036	0.014**	0.007*	
	(-3.31)	*(-2.16)*	*(0.34)*		*(-3.61)*	*(2.05)*	*(1.97)*	
Panel C: Earnings yield specification - Pearson (CO1) and Spearman (CO2) Correlations								
	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
CO1	0.000	0.018**	0.014**	0.013*	0.000	0.038**	0.032**	0.028*
t-stat	*(-0.00)*	*(2.17)*	*(2.30)*	*(1.94)*	*(-0.00)*	*(2.20)*	*(2.00)*	*(1.83)*
CO2	0.065***	0.043**	0.065***	0.085***	0.065***	0.096***	0.091***	0.086***
t-stat	*(3.21)*	*(2.14)*	*(3.24)*	*(5.06)*	*(3.21)*	*(5.39)*	*(5.44)*	*(5.12)*
N	34703	34703	34703	34703	34703	34703	34703	34703
Panel D: Earnings yield specification - Test significance of the Spearman correlation differences								
	Original sample				Winsorized sample			
	AF	LS	LAD	MM	AF	LS	LAD	MM
LS	0.022				-0.031**			
	(0.84)				*(-2.12)*			
LAD	0.000	-0.022			-0.026*	0.005		
	(-0.00)	*(-0.84)*			*(-1.95)*	*(1.08)*		
MM	-0.021	-0.043*	-0.021		-0.021	0.010	0.005*	
	(-1.50)	*(-1.69)*	*(-1.62)*		*(-1.53)*	*(1.48)*	*(1.90)*	

Table 7: Performance of quintile portfolios – Earnings per share specification: Non-GAAP earnings

This table presents the average percentage monthly returns (Ret: %) and abnormal returns (CAPM model: α_{CAPM} and Fama French model: α_{FF}) of quintile portfolios and high-low portfolios based on sorting earnings per share forecasts scaled by share price associated with analysts' forecasts (AF) and alternative estimators (LS, LAD and MM). Panel A shows the results when the original data are used to predict future earnings, while Panel B shows the results when the winsorized data are used to predict future earnings.

Panel A: Earnings per share specification - Original sample												
	AF			LS			LAD			MM		
Portfolios	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}
1	0.340	-0.605**	-0.662***	0.717	-0.264	-0.330	0.163	-0.824***	-0.888***	0.271	-0.721***	-0.795***
	(0.78)	*(-2.54)*	*(-3.02)*	*(1.56)*	*(-1.04)*	*(-1.60)*	*(0.37)*	*(-3.68)*	*(-4.58)*	*(0.58)*	*(-2.76)*	*(-3.47)*
2	0.493	-0.237**	-0.256**	0.475	-0.389*	-0.440**	0.415	-0.301***	-0.336***	0.367	-0.375***	-0.394***
	(1.62)	*(-2.01)*	*(-2.16)*	*(1.21)*	*(-1.84)*	*(-2.25)*	*(1.39)*	*(-2.64)*	*(-2.99)*	*(1.17)*	*(-2.90)*	*(-3.03)*
3	0.445	-0.121	-0.166*	0.431	-0.259**	-0.276**	0.451*	-0.143	-0.194	0.455*	-0.120	-0.158*
	(1.83)	*(-1.10)*	*(-1.76)*	*(1.48)*	*(-2.24)*	*(-2.52)*	*(1.78)*	*(-1.28)*	*(-2.01)*	*(1.86)*	*(-1.13)*	*(-1.69)*
4	0.493**	-0.054	-0.135	0.436*	-0.162	-0.212**	0.590**	0.052	-0.012	0.541**	-0.015	-0.093
	(1.98)	*(-0.40)*	*(-1.29)*	*(1.71)*	*(-1.48)*	*(-2.21)*	*(2.52)*	*(0.46)*	*(-0.14)*	*(2.17)*	*(-0.11)*	*(-0.87)*
5	0.637**	0.061	-0.025	0.860***	0.259	0.178	0.827***	0.282*	0.193	0.636***	0.064	-0.019
	(2.45)	*(0.43)*	*(-0.22)*	*(3.06)*	*(1.57)*	*(1.26)*	*(3.20)*	*(1.77)*	*(1.58)*	*(2.47)*	*(0.46)*	*(-0.18)*
High-low	0.297	0.666**	0.637**	0.143	0.524	0.508*	0.665**	1.106***	1.081***	0.365	0.785**	0.776***
	(0.92)	*(2.22)*	*(2.32)*	*(0.40)*	*(1.61)*	*(1.82)*	*(2.00)*	*(3.78)*	*(4.40)*	*(1.05)*	*(2.47)*	*(2.74)*
Panel B: Earnings per share specification - Winsorized sample												
1	0.340	-0.605**	-0.662***	0.498	-0.461*	-0.494**	0.382	-0.554**	-0.603***	0.270	-0.654***	-0.720***
	(0.78)	*(-2.54)*	*(-3.02)*	*(1.08)*	*(-1.68)*	*(-2.14)*	*(0.87)*	*(-2.16)*	*(-2.66)*	*(0.62)*	*(-2.60)*	*(-3.16)*
2	0.493	-0.237**	-0.256**	0.212	-0.564***	-0.563***	0.297	-0.437***	-0.449***	0.348	-0.395***	-0.411***
	(1.62)	*(-2.01)*	*(-2.16)*	*(0.63)*	*(-3.63)*	*(-3.72)*	*(0.96)*	*(-3.38)*	*(-3.46)*	*(1.10)*	*(-2.96)*	*(-3.06)*
3	0.445*	-0.121	-0.166*	0.417	-0.201**	-0.246***	0.400	-0.171	-0.213**	0.473*	-0.115	-0.153
	(1.83)	*(-1.10)*	*(-1.76)*	*(1.62)*	*(-2.02)*	*(-2.87)*	*(1.64)*	*(-1.60)*	*(-2.31)*	*(1.90)*	*(-1.08)*	*(-1.59)*
4	0.493**	-0.054	-0.135	0.564**	0.018	-0.037	0.558**	-0.001	-0.071	0.501**	-0.045	-0.118
	(1.98)	*(-0.40)*	*(-1.29)*	*(2.34)*	*(0.15)*	*(-0.37)*	*(2.24)*	*(-0.01)*	*(-0.67)*	*(2.04)*	*(-0.35)*	*(-1.17)*
5	0.637**	0.061	-0.025	0.814***	0.261*	0.159	0.723***	0.147	0.047	0.692	0.124	0.034
	(2.45)	*(0.43)*	*(-0.22)*	*(3.19)*	*(1.76)*	*(1.56)*	*(2.74)*	*(0.97)*	*(0.42)*	*(2.69)****	*(0.87)*	*(0.31)*
High-low	0.297	0.666**	0.637**	0.316	0.722**	0.654**	0.341	0.701**	0.650**	0.421	0.778**	0.753***
	(0.92)	*(2.22)*	*(2.32)*	*(0.85)*	*(2.05)*	*(2.28)*	*(1.01)*	*(2.16)*	*(2.31)*	*(1.29)*	*(2.48)*	*(2.66)*

Table 7: Performance of quintile portfolios – Earnings per share specification: Non-GAAP earnings (Contd.)

Panel C shows the differences between the average monthly returns (%) and the abnormal returns (α_{CAPM} , α_{FF} : %) of the high-low portfolio of the LAD estimator based on the original sample and those of analysts; the LS and MM estimators based on the original sample; and the LS, LAD and MM estimators based on the winsorized samples.

Panel C: Differences between the returns of the LAD estimator high-low portfolio based on the original sample and the returns of other portfolios

			Original sample		Winsorized sample		
		AF	LS	MM	LS	LAD	MM
Ret		0.368*	0.522**	0.300	0.349	0.323*	0.244
	t-stat	*(1.89)*	*(2.21)*	*(1.64)*	*(1.63)*	*(1.71)*	*(1.26)*
α_{CAPM}		0.440**	0.583**	0.321*	0.384*	0.405**	0.328*
	t-stat	*(2.29)*	*(2.43)*	*(1.75)*	*(1.75)*	*(2.12)*	*(1.70)*
α_{FF}		0.444**	0.574**	0.305*	0.428**	0.431**	0.328*
	t-stat	*(2.40)*	*(2.45)*	*(1.69)*	*(2.05)*	*(2.34)*	*(1.76)*

Table 8: Performance of quintile portfolios – Earnings yield specification: Non-GAAP earnings

This table presents the average percentage monthly returns (Ret: %) and abnormal returns (CAPM model: α_{CAPM} and Fama French model: α_{FF}) of quintile portfolios and high-low portfolios based on sorting earnings yield forecasts associated with analysts' forecasts (AF) and alternative estimators (LS, LAD and MM). Panel A shows the results when the original data are used to predict future earnings, while Panel B shows the results when the winsorized data are used to predict future earnings.

Panel A: Earnings yield specification - Original sample

	AF			LS			LAD			MM		
Portfolios	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}	Ret	α_{CAPM}	α_{FF}
1	0.409	-0.495**	-0.563***	0.499	-0.404*	-0.478***	0.360	-0.549**	-0.628***	0.444	-0.535**	-0.615***
	(1.00)	*(-2.39)*	*(-2.89)*	*(1.23)*	*(-1.91)*	*(-2.61)*	*(0.87)*	*(-2.53)*	*(-3.29)*	*(1.00)*	*(-2.30)*	*(-3.08)*
2	0.539*	-0.131	-0.155	0.395	-0.381**	-0.416***	0.547*	-0.153	-0.206	0.395	-0.310**	-0.360***
	(1.93)	*(-1.23)*	*(-1.50)*	*(1.16)*	*(-2.35)*	*(-2.69)*	*(1.80)*	*(-1.12)*	*(-1.59)*	*(1.29)*	*(-2.23)*	*(-2.62)*
3	0.452*	-0.108	-0.159	0.561*	-0.102	-0.170	0.551**	-0.054	-0.105	0.535**	-0.043	-0.077
	(1.83)	*(-0.86)*	*(-1.47)*	*(1.89)*	*(-0.71)*	*(-1.35)*	*(2.14)*	*(-0.50)*	*(-1.12)*	*(2.18)*	*(-0.41)*	*(-0.82)*
4	0.512**	-0.033	-0.115	0.585**	-0.011	-0.068	0.579**	-0.004	-0.061	0.603**	0.019	-0.048
	(2.06)	*(-0.24)*	*(-1.08)*	*(2.29)*	*(-0.10)*	*(-0.72)*	*(2.30)*	*(-0.03)*	*(-0.65)*	*(2.39)*	*(0.16)*	*(-0.53)*
5	0.679***	0.107	0.020	0.467	-0.141	-0.184	0.474*	-0.118	-0.163	0.545**	-0.051	-0.107
	(2.61)	*(0.75)*	*(0.18)*	*(1.71)*	*(-0.98)*	*(-1.35)*	*(1.83)*	*(-0.94)*	*(-1.40)*	*(2.08)*	*(-0.39)*	*(-0.92)*
High-low	0.270	0.601**	0.584**	-0.032	0.264	0.294	0.114	0.431*	0.465**	0.102	0.484*	0.508**
	(0.94)	*(2.28)*	*(2.33)*	*(-0.11)*	*(0.93)*	*(1.12)*	*(0.41)*	*(1.68)*	*(1.99)*	*(0.33)*	*(1.76)*	*(2.10)*

Panel B: Earnings yield specification -Winsorized sample

	AF			LS			LAD			MM		
1	0.409	-0.495**	-0.563***	0.426	-0.526**	-0.594***	0.400	-0.560**	-0.637***	0.457	-0.519**	-0.598***
	(1.00)	*(-2.39)*	*(-2.89)*	*(0.99)*	*(-2.43)*	*(-3.08)*	*(0.91)*	*(-2.42)*	*(-3.15)*	*(1.03)*	*(-2.24)*	*(-3.00)*
2	0.539*	-0.131	-0.155	0.419	-0.277**	-0.334***	0.401	-0.296**	-0.345***	0.404	-0.297**	-0.347**
	(1.93)	*(-1.23)*	*(-1.50)*	*(1.39)*	*(-2.02)*	*(-2.62)*	*(1.33)*	*(-2.25)*	*(-2.68)*	*(1.33)*	*(-2.14)*	*(-2.56)*
3	0.452*	-0.108	-0.159	0.532*	-0.093	-0.146	0.561**	-0.023	-0.059	0.507**	-0.066	-0.102
	(1.83)	*(-0.86)*	*(-1.47)*	*(1.97)*	*(-0.75)*	*(-1.39)*	*(2.26)*	*(-0.21)*	*(-0.62)*	*(2.08)*	*(-0.63)*	*(-1.09)*
4	0.512**	-0.033	-0.115	0.483*	-0.121	-0.182*	0.584**	-0.010	-0.075	0.649***	0.056	-0.006
	(2.06)	*(-0.24)*	*(-1.08)*	*(1.86)*	*(-1.06)*	*(-1.97)*	*(2.28)*	*(-0.08)*	*(-0.79)*	*(2.57)*	*(0.53)*	*(-0.07)*
5	0.679***	0.107	0.020	0.600**	0.023	-0.029	0.546**	-0.040	-0.097	0.538**	-0.056	-0.113
	(2.61)	*(0.75)*	*(0.18)*	*(2.37)*	*(0.19)*	*(-0.27)*	*(2.12)*	*(-0.32)*	*(-0.87)*	*(2.06)*	*(-0.43)*	*(-0.99)*
High-low	0.270	0.601**	0.584**	0.175	0.550**	0.564**	0.147	0.520*	0.540**	0.081	0.464*	0.485**
	(0.94)	*(2.28)*	*(2.33)*	*(0.60)*	*(2.20)*	*(2.52)*	*(0.49)*	*(1.93)*	*(2.23)*	*(0.26)*	*(1.68)*	*(1.99)*

Table 8: Performance of quintile portfolios – Earnings yield specification: Non-GAAP earnings (Contd.)

Panel C shows the differences between the average monthly returns (%) and abnormal returns (α_{CAPM} , α_{FF} : %) of the high-low portfolio of the LS estimator based on the winsorized sample and those of analysts; the LS, LAD and MM estimators based on the original sample; and the LAD and MM estimators based on the winsorized samples. Panel C shows the differences between the average monthly returns and abnormal returns of the high-low portfolio of analysts and those of the LS, LAD and MM estimators based on the original and winsorized samples.

Panel C: Differences between the returns of the LS estimator high-low portfolio of the winsorized sample and the rest

			Original sample			Winsorized sample	
		AF	LS	LAD	MM	LAD	MM
Ret		-0.095	0.207	0.061	0.073	0.028	0.094
	t-stat	*(-0.43)*	*(0.83)*	*(0.31)*	*(0.50)*	*(0.23)*	*(0.65)*
α_{CAPM}		-0.052	0.286	0.119	0.065	0.030	0.086
	t-stat	*(-0.23)*	*(1.14)*	*(0.61)*	*(0.46)*	*(0.25)*	*(0.61)*
α_{FF}		-0.019	0.271	0.100	0.056	0.024	0.079
	t-stat	*(-0.09)*	*(1.13)*	*(0.51)*	*(0.42)*	*(0.22)*	*(0.60)*

Panel D: Differences between the returns of analysts' high-low portfolio and the rest

		Original sample			Winsorized sample		
		LS	LAD	MM	LS	LAD	MM
Ret		0.302	0.156	0.169	0.095	0.123	0.189
	t-stat	*(1.21)*	*(0.62)*	*(0.89)*	*(0.43)*	*(0.64)*	*(0.99)*
α_{CAPM}		0.337	0.170	0.117	0.052	0.081	0.138
	t-stat	*(1.31)*	*(0.64)*	*(0.62)*	*(0.23)*	*(0.42)*	*(0.72)*
α_{FF}		0.290	0.119	0.076	0.019	0.043	0.099
	t-stat	*(1.17)*	*(0.46)*	*(0.44)*	*(0.09)*	*(0.24)*	*(0.57)*

Table 9: Properties of extreme observations: GAAP earnings

This table presents the average total assets (AST in $mil) of firms whose earnings, earnings per share or earnings yield are winsorized at 1st and 99th percentiles (Panel A) and the five most frequently appearing firms in the tails of the distributions of different earnings specifications. Freq denotes the number of years the company appears in the tail of the earnings distribution out of 30 years of yearly data.

Panel A: Average total assets of firms with extreme earnings observations

	AST($mil)	N
Total earnings specification	76,126.3	3149
Earnings per share specification	22,322.9	1961
Earnings yield specification	4,781.7	1694

Panel B: Most frequently appearing firms in the tails

	Freq.	AST($mil)
GAAP - Total earnings		
Coca-Cola Co	30	25,108.0
Exxon Mobil Corp	30	145,376.6
General Electric Co	30	390,609.9
Intl Business Machines Corp	30	87,809.0
AT&T Inc	28	97,228.2
GAAP - Earnings per share		
YRC Worldwide Inc	30	1,995.3
Washington Post	27	2,814.4
Berkshire Hathaway	25	151,864.1
American International Group	23	414,803.0
Tecumseh Products Co	23	1,183.1
GAAP- Earnings yield		
Kelly Services Inc	17	970.6
Baldwin & Lyons	16	595.8
Federal Agriculture MTG CP	15	6,271.3
Watsco Inc	15	485.6
Handy & Harman ltd	11	919.3

Table 10: Earnings forecast accuracy: GAAP earnings

This table presents time series averages of forecast errors (FE), absolute forecast errors (AFE) and root-mean squared errors (RMSE) associated with different estimators (LS, LAD and MM) for the original and winsorized samples and for different earnings specifications (total earnings, earnings per share and earnings yield). N denotes the number of observations.

		Original sample			Winsorized sample	
	LS	LAD	MM	LS	LAD	MM
Total earnings						
FE	-0.004	0.011	0.026	0.019	-0.001	0.007
t-stat	*(-0.04)*	*(0.62)*	*(1.54)*	*(0.32)*	*(-0.06)*	*(0.48)*
AFE	0.525***	0.197***	0.210***	0.300***	0.186***	0.195***
t-stat	*(6.62)*	*(6.60)*	*(7.21)*	*(5.76)*	*(7.33)*	*(7.65)*
RMSE	2.552***	1.787***	1.806***	1.467***	1.281***	1.350***
t-stat	*(3.80)*	*(2.75)*	*(3.10)*	*(3.65)*	*(3.22)*	*(3.42)*
N	75274	75274	75274	75274	75274	75274
Earnings per share						
FE	0.036	0.013	0.015	0.047**	0.009	0.007
t-stat	*(0.48)*	*(0.44)*	*(1.07)*	*(2.35)*	*(0.63)*	*(0.71)*
AFE	0.524***	0.221***	0.189***	0.166***	0.149***	0.150***
t-stat	*(7.11)*	*(5.76)*	*(7.05)*	*(6.96)*	*(7.60)*	*(8.88)*
RMSE	2.485***	1.682***	1.710***	0.546***	0.541***	0.545***
t-stat	*(4.61)*	*(3.21)*	*(2.75)*	*(5.66)*	*(5.76)*	*(7.13)*
N	74970	74970	74970	74970	74970	74970
Earnings yield						
FE	-0.018	-0.067***	-0.084***	-0.016	-0.067***	-0.087***
t-stat	*(-1.11)*	*(-5.53)*	*(-6.20)*	*(-1.02)*	*(-4.93)*	*(-5.65)*
AFE	0.268***	0.179***	0.176***	0.191***	0.173***	0.170***
t-stat	*(4.26)*	*(8.42)*	*(8.83)*	*(7.81)*	*(8.82)*	*(9.07)*
RMSE	2.133	3.137	3.120	1.121***	1.115***	1.118***
t-stat	*(1.07)*	*(0.41)*	*(0.40)*	*(2.88)*	*(2.86)*	*(2.87)*
N	69484	69484	69484	69484	69484	69484

Table 11: High minus low portfolio performance: GAAP earnings

This table presents the average monthly returns (%) and abnormal returns (%) (Fama-French three factors: α_{FF}) of the high minus low portfolios based on sorting earnings yield forecasts associated with different estimators (LS, LAD and MM) when different earnings specifications and different samples are employed.

	Original sample						Winsorized sample					
	LS		LAD		MM		LS		LAD		MM	
	Return	α_{FF}	Return	α_{FF}	Return	α_{FF}	Return	α_{FF}	Return	α_{FF}	Return	α_{FF}
Total earnings												
Ret	0.024	0.213	0.201	0.711**	0.255	0.676**	-0.419	-0.075	-0.003	0.436	0.105	0.508*
t-stat	*(0.08)*	*(0.75)*	*(0.49)*	*(2.29)*	*(0.65)*	*(2.21)*	*(-0.98)*	*(-0.24)*	*(-0.01)*	*(1.48)*	*(0.27)*	*(1.82)*
Earnings per share												
Ret	-0.323	-0.111	0.129	0.433	0.277	0.726**	-0.027	0.426	0.367	0.806***	0.257	0.677**
t-stat	*(-1.06)*	*(-0.43)*	*(0.37)*	*(1.52)*	*(0.71)*	*(2.40)*	*(-0.07)*	*(0.43)*	*(0.97)*	*(2.77)*	*(0.69)*	*(2.34)*
Earnings yield												
Ret	0.229	0.654	0.554	0.953***	0.474	0.885***	0.523	1.031***	0.500	0.950***	0.429	0.854***
t-stat	*(0.66)*	*(2.51)*	*(1.64)*	*(3.85)*	*(1.35)*	*(3.37)*	*(1.35)*	*(3.60)*	*(1.39)*	*(3.54)*	*(1.21)*	*(3.26)*